

Associative nature of event participation dynamics: a network theory approach

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Affiliation with various social groups can be a critical factor when it comes to quality of life of every individual, making these groups an essential element of every society. The group dynamics, longevity and effectiveness strongly depend on group's ability to attract new members and keep them engaged in group activities. It was shown that high heterogeneity of scientist's engagement in conference activities of the specific scientific community depends on the balance between the number of previous attendance and non-attendance and is directly related to scientist's association with that community. Here we show that the same holds for leisure groups of Meetup website and further quantify member's association with the group. We examine how structure of personal social networks is evolving with event attendance. Our results show that member's increasing engagement in group activities is primarily associated with the strengthening of already existing ties and increase of bonding social capital. We also show that Meetup social networks grow through big events while small events contribute to the group's cohesiveness.

INTRODUCTION

One of the consequences of the rapid development of the Internet and growing presence of information communication technologies is that large part of individuals daily activities, both off and online, is regularly recorded and stored. This newly available data granted us with a substantial insight into activities of a large number of individuals for a long period of time and led to development of new methods and tools which would enable better insight into dynamics of social groups [1]. The structure and features of social connections have both strong influence and depend on social processes such as cooperation [2, 3], diffusion of innovations [4, 5] and collective knowledge building [6]. Therefore, it is not surprising that complex network theory has proven to be very successful in uncovering mechanisms governing the behaviour of individuals and social groups [7, 8].

Human activity patterns as well as the structure of social networks and the emergence of collective behaviour in different online communities have been extensively studied in a last decade [6, 9–15]. On the other hand, dynamics of offline social groups, where the activities take place through offline meetings (events), have drawn relatively little attention given their importance. These groups, both professional and leisure ones, have large benefits and influence on everyday lives of individuals, their broader communities and society in general: they provide a social support for vulnerable individuals [16, 17], can be used for political campaigns and movements [18, 19], or can have an important role in career development [20]. As they have different purpose of their existence they also vary in structure of participants, dynamics of meetings and organisation. Some groups, such as cancer support groups or scientific conference communities, are intended for a narrow circle of people while others, leisure groups for instance, bring together people of all professions and ages.

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In pre-internet era these groups have been, by their organisation and means of communication between their members, strictly offline, while today we are witnessing the appearance of growing number of hybrid groups which combine both online and offline communication [19]. Although inherently different all these social groups have two main characteristics in common: they don't have formal organisation, although their members follow certain written and non-written rules, and the membership in them is on a voluntary basis. Bearing this in mind it is clear that the function, dynamics and longevity of these self-organised communities depend primarily on their ability to attract new and retain old members active in the group activities. Understanding the reasons and detection of key factors which influence members to remain active in social group dynamics are thus important, especially having in mind their relevance for the broader social communities and society.

In previous work [20] we have shown that the scientists participation patterns in conference series are not random and that they exhibit an universal behaviour independent of conference subject, size or location. Using the empirical analysis and theoretical modelling we have shown that the scientist's conference attendance depends on the balance between the number of previous attendance and non-attendance and argued that this repetitiveness is driven by her association with the conference community, i.e. with the number and strength of social ties with other conference community members. We also argued that similar behaviour when it comes to member's participation patterns in organised group events can be expected in other social communities. Here we provide the empirical evidence supporting these claims and further investigate the relationship between dynamics of individuals participation in social group activities and structure of its social network. Meetup portal, whose group dynamics we are studying, is an event-based social network. Meetup members use the online communication for the organisation of offline gatherings. The online availability of the event attendance lists and group membership enables us to examine the event participation dynamics of the Meetup groups and its influence on the structure of social networks between group members. The diversity of Meetup groups in terms of the type of activity and size allows us to further examine and confirm the universality of member's participation patterns. The previous works using Meetup source of data have been mostly focused on event recommendation problem [21–25] and the structural properties of social networks and relationships between event participants [25, 26] by disregarding evolutionary behaviour of Meetup groups.

In this work, we examine the event induced evolution of social networks for four large Meetup groups from different categories. Like in the case of conference participation, we study the probability distribution of total number of meetup attendance and show that it also exhibits a truncated power law for all four groups, like in the case of conference participation dynamics [20]. This finding suggests that event participation dynamics of Meetup groups is characterised by positive feedback mechanism, which is of social origins and is a directly related to member's association with the social community of the specific Meetup group. Using complex network theory we examine in more details the correlation between member's decision to participate at an event and her association with other members of that Meetup group. Specifically, we track how member's connectedness with community changes with the number of attendance by measuring the change in clustering coefficient and relation between degree and strength in evolving weighted social network, where only statistically significant connections are considered. Our results indicate that greater involvement in group activities is more associated with the strengthening of the existing than to creation of new ties. This is consistent with previous research on Meetup which has shown that repeated event attendance leads to increase of bonding and decrease of bridging social capital [27, 28]. Furthermore, in view of the fact that people interact and network evolves through events, we examine how particular event affects the network size and structure. We investigate effect of event size and time ordering on social network organization by studying the change in network topology, number of distinctive

links and clustering, caused by the removal of specific event and find that the purpose of large events is to facilitate new connections, while during the small events already acquainted members strengthen their interpersonal ties. Similar behaviour was observed at the level of communities, where small communities are typically closed for new members, while contrary to this, the change of membership in large communities is favourable [29, 30].

This paper is organized as follows: we first study the distribution of the total number of participations for four Meetup groups from different categories. Next we introduce filtered weighted social network to characterize significant social connections between members and discuss its structural properties. Specifically, we study how the local topological properties evolve with the growth of the number of participations in order to derive relationships between the member association with the group and activity patterns. In order to analyse impact of the particular event on the network organization, we remove events using different strategies and show how it influences social structure.

RESULTS

Event participation patterns of Meetup groups

Meetup is the online social networking platform which enables people with common interest to start a group with purpose of arranging the offline meetings (events, meetups) all over the world. The groups have various topics and are sorted into 33 different categories, such as careers, hobbies, socializing, health, etc. These groups are of various sizes, have different event dynamics and hierarchical organisation. They also differ in type of activity members engage, ranging from socialising events, like parties and clubbing, to professional trainings, such as seminars and lectures. Common to all groups is the way they organise offline events: each member of the group gets an invitation to event to which she replies with yes/no, creating in that way a record of attendance for each event. We use this information to analyse event participation patterns and to study the evolution of social network.

Here, we analyse four large groups, each having more than three thousand organized events, (see Methods and Table I), from four different categories. We chose these four groups because of their convenience for statistical analysis, large number of members and organised events, and also for the fact that they are different when it comes to the type of activity and interest their members share. The *geamelt* (GEAM) group is made of *foodie thrill-seekers* who mostly meet in the restaurants and bars in order to try out new exciting foods and drinks, while people in *VegasHiker* (LVHK) are hikers who seek excitement through physical activity. The *Pittsburgh-free* (PGHF) is a group which invites its members to free, or almost free, social events, and the *TechLife Columbus* (TECH) is about social events that focus on tech community networking, entrepreneurship, environmental sustainability, and professional development.

Figure 1 shows that the probability distributions of the total number of members attendance of group events for all four groups exhibits truncated power law behaviour, with power law exponent larger than one. Power law and truncated power-law behaviour of the probability distributions can be observed for the number of and the time lag between two successive participations in group organised events, Fig S1 and Fig S2 in SI. In fact, we find that the similar participation patterns (they differ in the value of exponents) can be observed for all Meetup groups, regardless of their size, number of events or category. As in the case of conference participation dynamics [20], this indicates that the probability to participate in the next event depends exclusively on the balance of the number of previous participations and non-participations. We argued in [20] that forces behind conference participation dynamics are of social origin, and it follows from the Fig 1 that the same

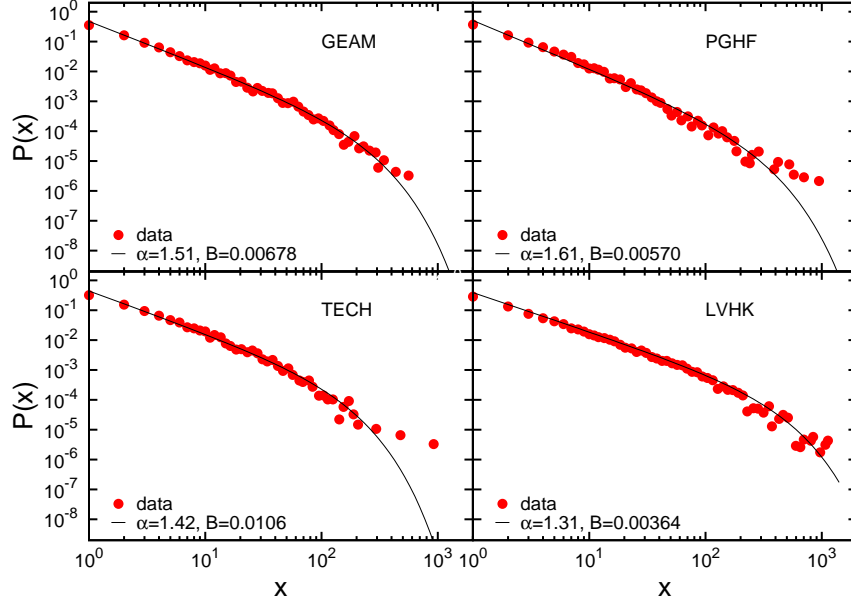


FIG. 1. **The total number of attended events.** The probability distribution of total number of participations for four Meetup groups. The solid line represents best fit to truncated power law distribution, $x^{-\alpha}e^{-Bx}$.

can be argued in the case of Meetup group participation dynamics. The more participations in group activities member has, the stronger and more numerous are her connections to the other group members, and thus her association with the community. We further explore this assumptions by investigating the event driven evolution of the social networks of the four different Meetup groups.

Structure of social event-based network

We construct the social network between group members, for each separate groups, as a network of co-occurrence on the same event (see Methods for more details). By definition these networks are weighted networks where the link weight between two members is equal to the number of events they participated together. These networks are very dense, which is a direct result of construction method, with broad distribution of link weights (see Fig S3 in SI). Co-occurrence at the same event doesn't necessarily imply a relationship between two members. For instance, a member of the group that attends many events, or big events, has large number of acquaintances, and thus large number of social connections, which are not of equal importance when it comes to her association with the community. Similarly, two members that attend large number of events can have relatively large number of co-occurrences which can be the result of coincidence and not an indicator of their strong relationship. In order to filter out these less important connections we use filtering

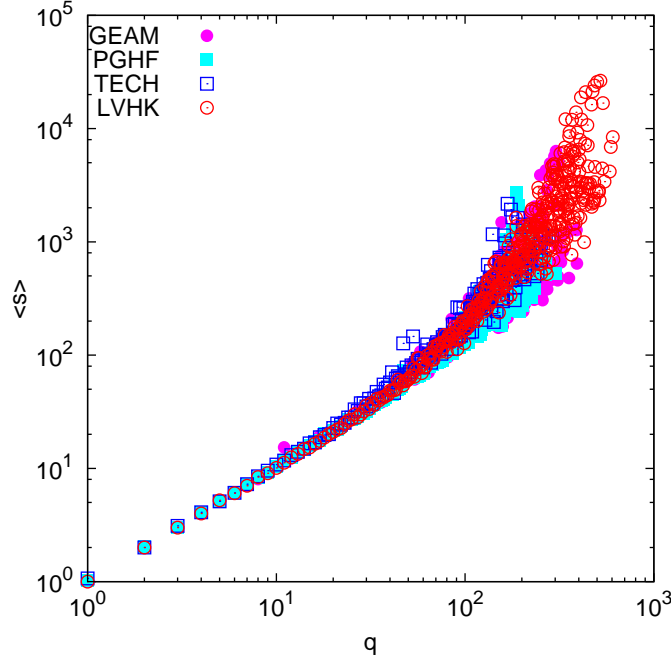


FIG. 2. **Node strength dependence on node degree.** The dependence of average member's strength on her degree in social network of significant links for considered groups.

technique based on configuration model for bipartite networks [31, 32] (see Methods). By applying this technique to weighted networks we reduce their density and put more emphasis on the links which are less likely to be the result of coincidence. This way we put more emphasis on the links of higher weight without the removal of all links with weight smaller than certain threshold (see Fig S3 in SI), a standard procedure for network pruning. We explore the evolution of these social networks of significant relationships between Meetup group members by studying how the local characteristics of the nodes (members) are changing with their growing number of participations in group activities.

Association with the community of the specific Meetup group can be quantitatively expressed through several local and global topological measures of weighted networks. Specifically, we explore how the number of significant connections (member's degree) and their strength (member's strength), as well as how member's embeddedness in the group (non and weighted clustering coefficient) are changing with the number of attended group events. Figure 2 shows how average strength of a node depends on its degree in filtered networks of four selected Meetup groups. While the degree equals to the number of member's significant social relationships, the strength measures how strongly she is connected to the rest of the group [33]. In all considered Meetup groups members with small and medium number of acquaintances ($q \leq 50$) have similar value of strength and degree, i.e. their association with the community is described by the number of people they know, not from the strength of their connections (see Fig 2). Having in mind that the average size of the event in these four groups is less than 20, we can conclude that majority of member with degree less than 50 are the ones that attended only few group meetups. Previous study [24] has

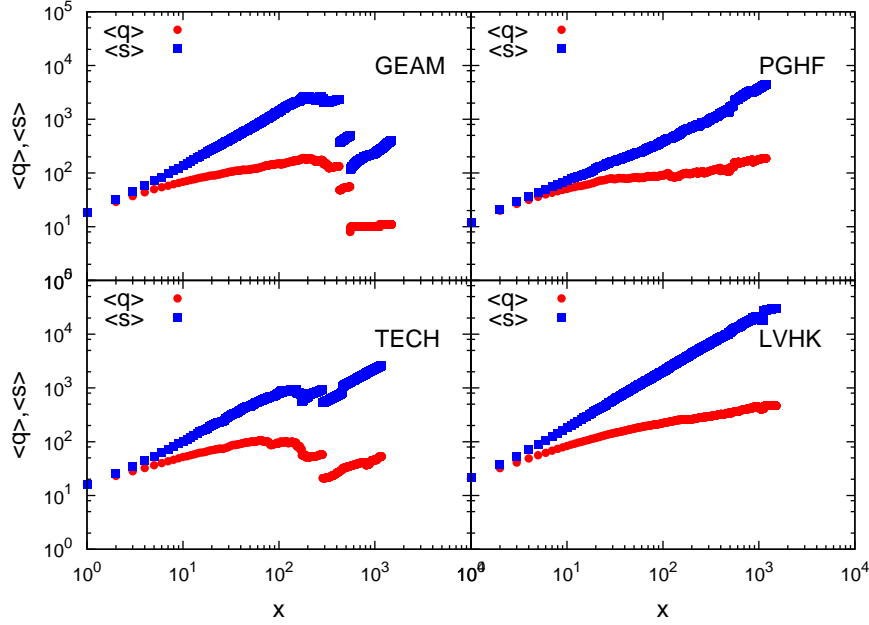


FIG. 3. **The event driven evolution of member's degree and strength.** Dependence of member's average degree and strength on the number of attended events for four considered Meetup groups.

found that the probability for a member to attend the group events strongly depends on weather her friends will also attend. The non-linear relationship between degree and average strength for $q > 50$ shows that event participation of already engaged members (ones who already attended few meetings) is more linked to strength of social relations than to their number. This means that at the beginning of their engagement in group activities, when the associations is relatively small, the participation is conditioned with the number of members a person knows, while later, when the associations becomes stronger, the intensity of relations with already known members becomes more important.

This finding is further supported by the change of average degree and strength with the number of participations. Figure 3 shows how the degree and strength evolve with the number of participations in group events averaged over all members. At the beginning, the degree and strength have the same value and grow at the same rate, but after only few participations the strength becomes larger than degree, and starts to grow much faster for the members of all four Meetup communities. After 100 attended events the average strength of a member is up to ten times larger than her degree (see Fig S4 in SI). This indicates that the event participation dynamics is mostly governed by the need of the member to maintain and strengthen her relationships with the already known members of the community. As a matter of fact, our analysis of member's embeddedness in social network shows that it is not about maintaining the strong relations with single members of community, but rather with the small subgroups of members. The relatively high value average clustering coefficient, $\langle c_i \rangle$, shown in Fig 4 indicates that there is a high probability (more than 10% on average) that

friends of member also form significant relationships. The slow decay of $\langle c_i \rangle$ with the number of participations and the fact that it remains relatively large (above 0.2) even for participants with thousand attended meetups, Fig 4, shows that personal networks of members have tendency to remain clustered, i.e. have relatively high number of closed triplets compared to random networks.

We further examine the structure of these triplets and its change with the number of participations by calculating the averaged weighted clustering coefficient. The weighted clustering coefficient, c_i^W measures the local cohesiveness of the personal networks by taking into account the intensity of interactions between local triplets [33]. This measure does not just take into account the number of closed triplets of the node i but also their total relative weight with respect to the total strength of the nodes (see Methods). We examine how its value, averaged over all participants that have attended x events, is changing with the number of attended events $\langle c_i^W \rangle(x)$. As it is shown in Fig 4 the member's network of personal contacts shows high level of cohesiveness, on the average. Like its non-weighted counterpart, the value of $\langle c_i^W \rangle$ only slightly declines during member's early involvement in group activities, while later it remains constant and independent of the number of participations. The comparison of weighted and non-weighted clustering coefficients reveals an information about the role of strong relationships in the local network, i.e. whether they form triplets or bridges between different cohesive groups [33]. At the beginning of member's involvement in the group, these two coefficients have similar value, Fig 4, which indicates that the cohesiveness of subgroup of personal contacts is not that important for early participation dynamics. As the number of attended events grows, as well as the number and strength of personal contacts, the weighted clustering coefficient becomes larger than its non-weighted counterpart, indicating that member's strongest ties are with the other members who are also friends. The fact that in latter engagement weighted clustering coefficient is larger than its non-weighted counterpart indicates that clustering has an important role in network organisation of Meetup groups and thus in the group participation dynamics [33].

Event importance in group participation dynamics

In the previous work [20] we have shown that the conference participation dynamics is independent of conference topic, type and size. The same holds true for Meetup participation dynamics, i.e. the member's participation patterns in the Meetup group activities do not depend on the group size, category, location or type of activity. However, the size of group events and their time-order may influence the structure of network and thus group dynamics. We explore how topological properties of the networks, specifically the number of acquaintances and network cohesion, change after the removal of events according to certain order (see Methods for details).

Firstly, we study how the removal of events according to certain order influence the number of overall acquaintances in the network. For this purpose we define measure η (see Methods) which we use to quantify the percentage of the remaining significant acquaintances after the removal of event. Figure 5 shows the change of measure η after the removal of r fraction of events according to chosen strategy. We see that the most of the new significant connections are usually made on the largest events. The importance of large events for the creation of new acquaintances is especially striking for three groups GEAM, PGHF, and TECH, where about 80% of acquaintances only met at the 20% of the largest events. For LVHK the decrease is slower, probably due to a difference in event size fluctuations (see Fig S5 in SI), but still more than 50% of acquaintances disappear if we remove 40% of the largest events, which is still much higher percentage of contacts compared to random removal of events (see Fig 5 (right)). Similar results are observed when we remove events from the

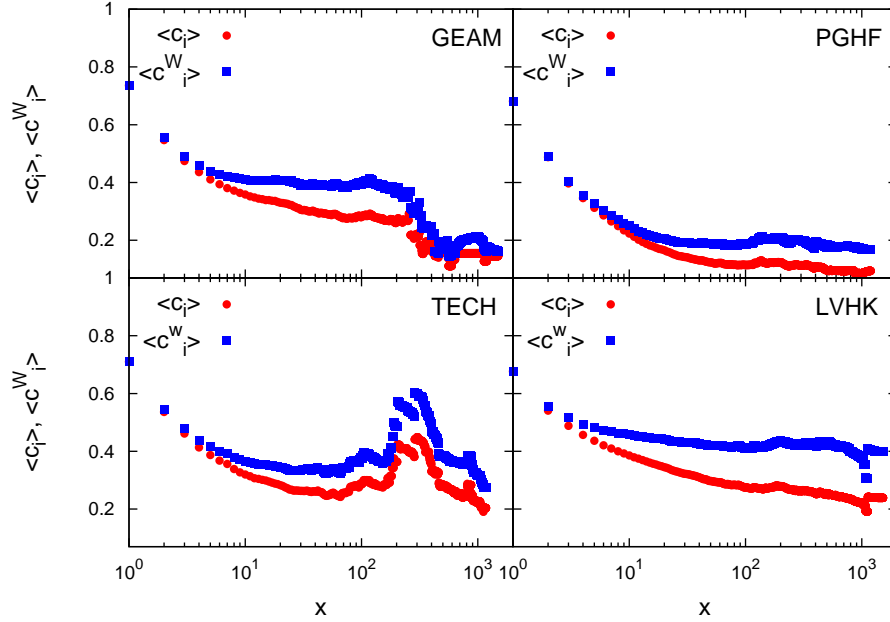


FIG. 4. **The local cohesiveness of social network of significant links.** The evolution of members subgroup cohesiveness, measured with averaged non-weighted $\langle c_i \rangle$ and weighted clustering coefficient $\langle c_i^W \rangle$, with the number of attended events.

smallest to largest, Fig 5 (left). Only 20% of acquaintances are being destroyed by removing 80% of the smallest events, for all four groups. This indicates that the new, weak, connections ties are usually formed during large events, while these weak, already existing, acquaintances are further strengthen during smaller meetups. On the other hand, the removal of events according to their temporal order, Fig 5, has very similar effect as random removal, i.e. the value of parameter η decreases gradually as we remove events.

Similar conclusions can be drawn from change of average weighted clustering coefficient with the removal of events, Fig 6. Removal of events in ordering from the smallest to the largest, doesn't result in the significant change of $\langle C^W \rangle$ (now averaged over all nodes in the network). The same value of weighted clustering coefficient, even after removal of 80% of events, shows that small events are not attended by a *pair of* but rather by a *group* of old friends. On the other hand, the removal of events from the largest to the smallest results in gradual decrease of $\langle C^W \rangle$. A certain fraction of triads in the network are made by at least one low weight link, and they are being the first one destroyed by the removal of the largest events, leading to gradual decrease of $\langle C^W \rangle$. Removal of events according to their temporal order results in the change of $\langle C^W \rangle$ similar to one obtained with random removal of events confirming further that the time-ordering of events doesn't have an influence on the network structure.

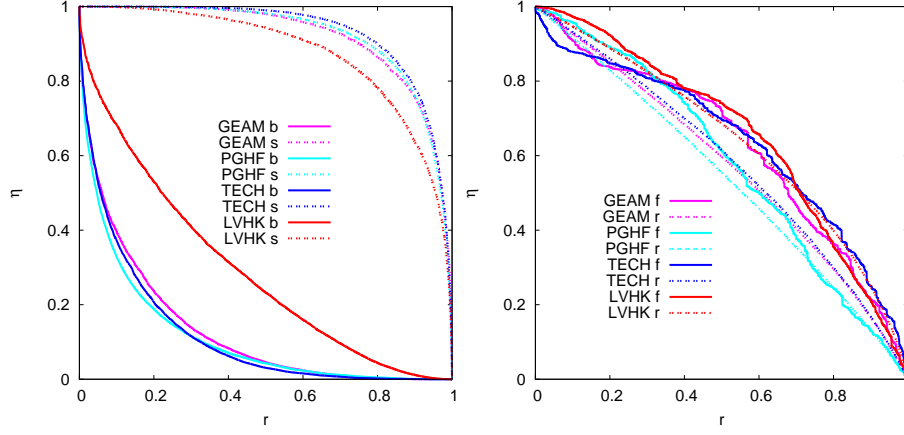


FIG. 5. **The importance of event size for number of distinctive links in the network.** The change of η with the removal of events according to their size (left) and time order and random (right). Abbreviations indicate the order in which we remove events: **b** -from the largest to the smallest, **s** from the smallest to the largest, **f** from the first to the last and **r** random.

DISCUSSION AND CONCLUSION

In this article we explore event participation dynamics and underlying social mechanism of Meetup groups. The motivation behind this was to further explore event-driven dynamics, work we started by exploring participation patterns of scientists at scientific conferences [20], and to better examine the social origins behind the repeated attendance of the group events, which was not feasible with the conference data. The results in this manuscript are based on empirical analysis of participation patterns and topological characteristics of networks for four different Meetup groups made up of people with different motives and readiness to participate in group activities: GEAM, PGHF, TECH, LVHK.

Although these four groups differ in category and type of activity, we have shown that all four of them are characterised with similar participation patterns: the probability distribution of total number of participations, number of successive participations and time lag between two successive participations follow the power-law and truncated power law behaviour with the value of power law exponents between 1 and 3. The resemblance of these patterns with the ones observed for conference participation [20] indicates that these two, seemingly different, social system dynamics are governed by similar mechanism. This means that the probability for a member to participate at the future events depends non-linearly on the balance between the number of previous participations and non-participations. As in the case of conferences [20] this behaviour is independent of group

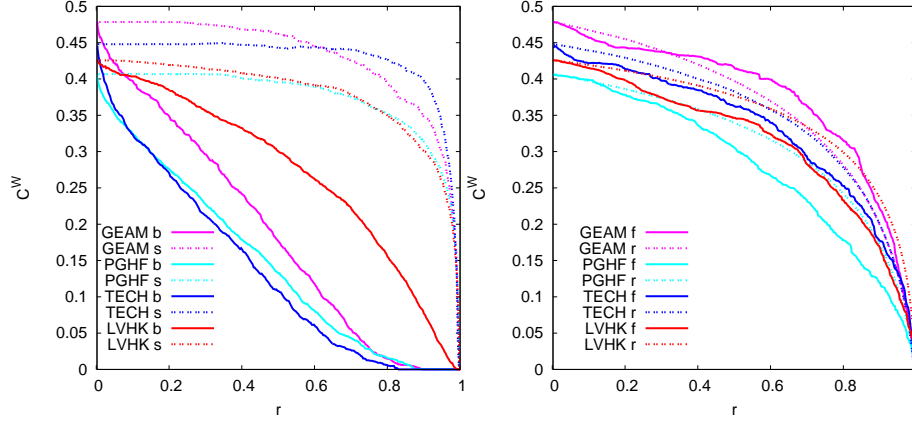


FIG. 6. **The importance of event size for the network cohesiveness.** The change of local network cohesiveness with removal of events according to their size (left) and time order and random (right). Abbreviations indicate the order in which we remove events: **b** -from the biggest to smallest, **s** from the smallest to the biggest, **f** from the first to the last and **r** random.

category, size, or location meaning that members association with the community of Meetup group strongly influence their event participations patterns and thus the frequency and longevity of their engagement in group activities.

The member's association with the community is primarily manifested through her interconnectiveness with other members of the specific Meetup group community, i.e. in the structure of her personal social network. We have examined topological properties of filtered weighted social network constructed from the members event co-occurrence. By filtering the network we emphasized the importance of significant links, ones which are not the result of coincidence but rather an indicator of existing social relations. The analysis of local topological properties of these networks has revealed that strength of connectedness with the community for the members with small number of participations is predominantly the consequence of the width of their social circles. The average strength and degree of members with $q \lesssim 50$, which on average corresponds to only a few participations, are equal, while the strength of members who know more than 50 people and have participated in more than a few events, is several times higher than their degree. This means that strengthening of existing ties becomes more important than meeting new people after a few participations. These arguments are further extended with our observation of the evolution of average strength and degree with the growth of number of participations. Both, average degree and strength grow, but the growth rate of strength is higher than degree for all four Meetup groups. All four groups are characterised with very high cohesiveness of their social communities. The evolution of

clustering coefficients, non and weighted one, and their ratio show that bonding with community becomes more important as the members engagement in group activity progress. As in the case of conference participation, frequent attendees of group activities tend to form a core whose stability grows with the number of participations [20, 34]. The need of frequent attendees to maintain and increase their bonding with the rest of the community influences their probability to attend future meetings and thus governs the event participation dynamics of the Meetup groups.

While group category, type of activity and size don't significantly affect the participation dynamics in group activities and network structure, the size of separate events organised in groups does have an influence on the evolution of social networks. Large events represent an opportunity for members to make new acquaintances, i.e. to establish new connections, while small meetings are typically the gatherings of members with preexisting connections and their main purpose is to facilitate the stronger bonding among group members. While the size of the event influence structure of social networks, it turns out that their time-order is irrelevant for group dynamics.

The universality of members event participation patterns, shown in this and previous work [20], and its socially driven nature give us a better insight not only about the dynamics of studied social communities but also about others which are organised on very similar principles: communities that bring together people with the similar interests and where the participation is voluntary. Having in mind that these type of groups constitute a large part of human life, including all life aspects, understanding their functioning and dynamics is of great importance. Our results not only contribute to the corpus of increasing knowledge but also indicate the key factor which influences the group longevity and successful functioning: the association of group members with the community. This and recent success stories [35] suggest that complex network theory can be an extremely useful tool in creating successful communities. Future studies will be conducted towards further confirmation of universality of event-participation patterns and better understanding of how social association and contacts can be used for creating conditions for successful functioning of learning and health support groups.

MATERIALS AND METHODS

Data

There are more than 240000 groups in 181 countries classified into 33 categories. For each of selected four groups, we have collected list of events organized by the group and information on members who confirmed their participation in the given event since the group's beginnings. Each member has a unique id which enables us to follow her activity in group events during the time. More details about the group sizes and the number of events is given in Table I.

Meetup group	Acronym	Category	N_m	N_e
geamcIt	GEAM	Food & Drink	5377	3986
pittsburgh-free	PGHF	Socializing	4995	4617
techlifecolumbus	TECH	Tech	3217	3162
VegasHikers	LVHK	Outdoors & Adventure	6061	5096

TABLE I. Summary of collected data for four selected Meetup groups. N_m is the total number of group members while N_e is the total number of organised events.

Network construction and filtering

Network construction We start with a bipartite member-event network represented with participation matrix B . Let N_m denotes total number of members in the group and N_e is the total number of the events organized by the group. If the member i participated in the event l element of matrix B_{il} takes a value 1, otherwise $B_{il} = 0$. In the bipartite network created in this way, the member's degree is equal to the total number of events member participated in, while the event's degree is defined as the total number of members that have attended that event. The social network, which is the result of members interactions during the Meetup events and is represented by weighted matrix W , is created from the weighted projection of bipartite network to the member partition [36, 37]. In the obtained weighted network nodes correspond to individual members while the value of the element of weighted matrix, W_{ij} , corresponds to the number of common events two members have attended together.

Network filtering The observed weighted network is the dense network where some of the non-zero edges can be the result of coincidence. For instance, these edges can be found between members who attended large number of events or events with many participants, and therefore they do not necessarily indicate social connections between members. The pruning of these type of networks and separation of significant edges from the non-significant ones is not a trivial task [31, 32, 38]. For this reasons we start from the bipartite network and use the method that determines the significance of W_{ij} link based on configuration model of random bipartite network [31, 32, 39, 40]. In this model of random networks, the event size and the number of events a member attended are fixed, while all other correlations are destroyed (see SI for further explanations). Based on this model, for each link in bipartite network, B_{il} , we determine the probability p_{il} that user i has attended the event l . The assumption of uncorrelated network enables us to also estimate the probability that two member, i and j , have attended the same event, which is equal to $p_{il}p_{jl}$. The probability that two members have attended the same w events is then given by Poisson binomial distribution

$$P_{ij}(w) = \sum_{M_w} \prod_{l \in M_w} p_{il}p_{jl} \prod_{l \notin M_w} (1 - p_{il}p_{jl}) \quad (1)$$

where M_w is the subset of w events that can be chosen from given M events [31, 32, 41]. We define p -value as the probability that two members i and j has co-occurred on at least w_{ij} events, i.e. that the link weight between these two members is w_{ij} or higher

$$p\text{-value}(w_{ij}) = \sum_{w \geq w_{ij}} P_{ij}(w). \quad (2)$$

The relationship between users i and j will be considered statistically significant if $p\text{-value}(w_{ij}) \leq p_{trs}$. In our case, threshold $p_{trs} = 0.05$. All links with $p\text{-value}(w_{ij}) > p_{trs}$ are the consequence of chance and are considered as non-significant and thus removed from the network. This way we obtain weighted social network of significant relations between members of the Meetup group W_{ij}^S . The details on how we estimate p_{il} and $P_{ij}(w)$ for each link are given in SI.

Topological measures All topological measures considered in this work are calculated for weighted social network of significant relations W_{ij}^S . We consider the following topological measures of the nodes:

- The node degree $q_i = \sum_j \mathcal{H}(W_{ij}^S)$, where \mathcal{H} is Heaviside function ($\mathcal{H}(x) = 1$ if $x > 0$ otherwise $\mathcal{H}(x) = 0$);

- The node strength $s_i = \sum_j W_{ij}^S$ [7];
- Non-weighted clustering coefficient of the node $c_i = \frac{1}{q_i(q_i-1)} \sum_{j,m} \mathcal{H}(W_{ij}^S) \mathcal{H}(W_{im}^S) \mathcal{H}(W_{jm}^S)$ [7].
- Weighted clustering coefficient of the node $c_i^W = \frac{1}{s_i(q_i-1)} \sum_{jm} \frac{W_{ij}^S + W_{im}^S}{2} \mathcal{H}(W_{ij}^S) \mathcal{H}(W_{im}^S) \mathcal{H}(W_{jm}^S)$ [33].

The weighted clustering coefficient of the network, $\langle C^W \rangle$, and its non-weighted counterpart, $\langle C \rangle$, are values averaged over all nodes in the network.

The event relevance

In order to explore the relevance of event size and time ordering in evolution of social network topology we analyse how removal of events, according to specific ordering, influence the number of acquaintance and network cohesion. Specifically, we observe the change of measure η , which represents the fraction of the remaining acquaintances, and weighted clustering coefficient, $\langle C^W \rangle$, after the removal of certain fraction of events. The removal of event results in the change of the link weights between group members. For instance, if two members, i and j , have participated in the event l , the removal of this event will result in the decrease of the link weight W_{ij}^S by one. The further removal of events in which these two members have co-occurred will eventually lead to termination of their social connection, i.e. $W_{ij}^S = 0$. If $W^S(r)$ is the matrix of link weights after the removal of fraction of r events and W^S is the original matrix of significant relations, then the value of parameter η after the removal of r events is calculated as

$$\eta(r) = \frac{\sum_{ij} \mathcal{H}(W_{ij}^S(r))}{\sum_{ij} \mathcal{H}(W_{ij}^S)}, \quad (3)$$

The value of weighted clustering coefficient, $\langle C^W \rangle$, after the removal of fraction of r events is calculated using the same formula as for the $\langle C^W \rangle$ just using the value of $W^S(r)$ instead of W^S .

We remove events according to several different strategies:

- We sort events by the number of participants. Then, we remove sorted events in both, descending and ascending order.
- We sort events by arrangement in time. We remove sorted events in direct order.
- We remove events in random order. We perform this procedure for each list of events 100 times.

ACKNOWLEDGMENTS

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SUPPORTING INFORMATION

A. Network filtering

The Meetup dataset, containing information on organised events by certain Meetup group and members of that group that confirmed attendance at an event, allows us to construct member-event bipartite network with adjacency matrix B . For each member $i \in \{1, \dots, N\}$ and event $l \in \{1, \dots, M\}$, matrix element $B_{il} = 1$ if member i participated event l , or $B_{il} = 0$, otherwise. The degree of member i is defined as the total number of events member i participated in, $k_i = \sum_l B_{il}$, and similarly, the degree of event l is defined as the total number of members attended the event, $d_l = \sum_i B_{il}$. Given the matrix B , social relations between Meetup members can be analysed using the projected unipartite member-member weighted network, where the weight of the link between two members is equal to the number of events they both attended. The observed weighted network is the dense network where some of the non-zero edges can be a matter of coincidence. For instance, two frequent attendees can meet several times due to a chance not due to the fact that there is some relation between them, which means that the connection between them is not significant for our analysis. Also, the connections between members that meet at big events and never again can not be regarded as social relations and thus they need to be excluded from our analysis. To make the distinction between significant and non-significant edges is nontrivial task [31, 32, 38]. Here we use the method which enables us to calculate the significance of the link between two members based on the probability for that link to occur in random network. As a null model we use configuration model of bipartite network [31, 32, 39, 40].

First we describe general framework for constructing randomized network ensemble \mathcal{G} with given structural constraints $\{x_i\}$. The maximum-entropy probability of the graph in the ensemble, $P(G)$, is given by

$$P(G) = \frac{1}{Z} e^{-\sum_i \lambda_i x_i}, \quad (4)$$

where the λ_i are Lagrangian multipliers and the partition function of these network ensembles is defined as

$$Z = \sum_G e^{-\sum_i \lambda_i x_i}. \quad (5)$$

The ensemble average of a graph property x_i can be expressed as

$$\langle x_i \rangle = \sum_G x_i(G) P(G) = -\frac{\partial}{\partial \lambda_i} \ln Z. \quad (6)$$

Then the constants λ_i could be determined from (6).

Let us now consider configuration model of the member-event bipartite network with given degree sequence k_i and d_l . In this case the partition function can be written as

$$Z = \sum_G e^{-\sum_i \alpha_i k_i - \sum_l \beta_l d_l} = \sum_G e^{-\sum_{il} (\alpha_i + \beta_l) B_{il}} = \prod_{il} (1 + e^{-(\alpha_i + \beta_l)}). \quad (7)$$

The Lagrangian multipliers α_i and β_l are determined from

$$k_i = -\frac{\partial}{\partial \alpha_i} \ln Z = \sum_{l=1}^M \frac{e^{-\alpha_i - \beta_l}}{1 + e^{-\alpha_i - \beta_l}}, \quad (8)$$

$$d_l = -\frac{\partial}{\partial \beta_l} \ln Z = \sum_{i=1}^N \frac{e^{-\alpha_i - \beta_l}}{1 + e^{-\alpha_i - \beta_l}}. \quad (9)$$

Finally, we can calculate the probability p_{il} that a member i attended event l . If we define coupling parameter $\lambda_{il} = \alpha_i + \beta_l$ and write partition function in the form

$$Z = \sum_G e^{-\sum_{il} \lambda_{il} B_{il}} = \prod_{il} (1 + e^{-\lambda_{il}}), \quad (10)$$

then, it holds

$$p_{il} = \langle B_{il} \rangle = -\frac{\partial}{\partial \lambda_{il}} \ln Z = \frac{e^{-\lambda_{il}}}{1 + e^{-\lambda_{il}}} = \frac{e^{-\alpha_i - \beta_l}}{1 + e^{-\alpha_i - \beta_l}}. \quad (11)$$

Now, when the probability p_{il} is given, the probability that members i and j both participated in event l is $p_{ij}(l) = p_{il}p_{jl}$. The probability $P_{ij}(w)$ of having an edge of the weight w between the nodes i and j is given by Poisson binomial distribution

$$P_{ij}(w) = \sum_{M_w} \prod_{l \in M_w} p_{ij}(l) \prod_{\bar{l} \notin M_w} (1 - p_{ij}(\bar{l})), \quad (12)$$

where M_w is the subset of w events that can be chosen from given M events [31, 32, 41]. We use DFT-CF method (Discrete Fourier Transform of characteristic function), proposed in [42], to compute Poisson binomial distribution.

On the basis of $P_{ij}(w)$, we define p -value as the probability that edge (i, j) has weight higher or equal than w_{ij}

$$p\text{-value}(w_{ij}) = \sum_{w \geq w_{ij}} P_{ij}(w). \quad (13)$$

The edge (i, j) will be considered statistically significant if $p\text{-value}(w_{ij}) \leq \alpha$. In our case, threshold $\alpha = 0.05$. If $p\text{-value}(w_{ij}) > \alpha$, the edge (i, j) should be removed as spurious statistical connection between members (set $w_{ij} = 0$).

B. Figures

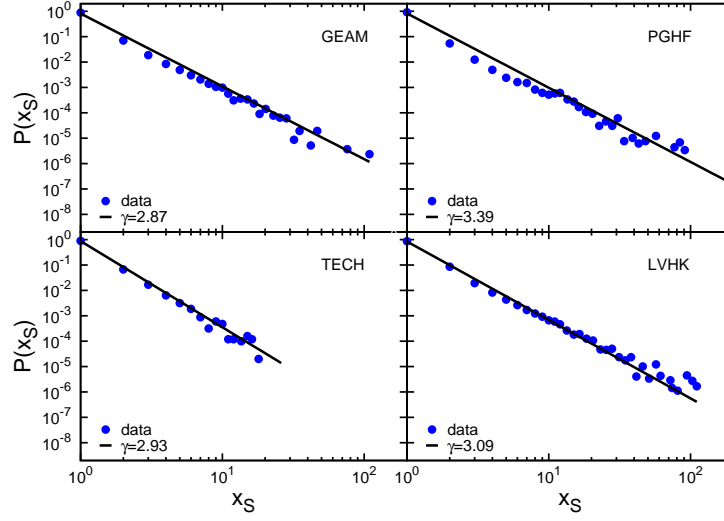


FIG. S1. The probability distribution of successive number of participations in group events, x_S , for four selected Meetup groups. The probability distribution follows power-law behaviour $P(x_S) \sim x_S^{-\gamma}$.

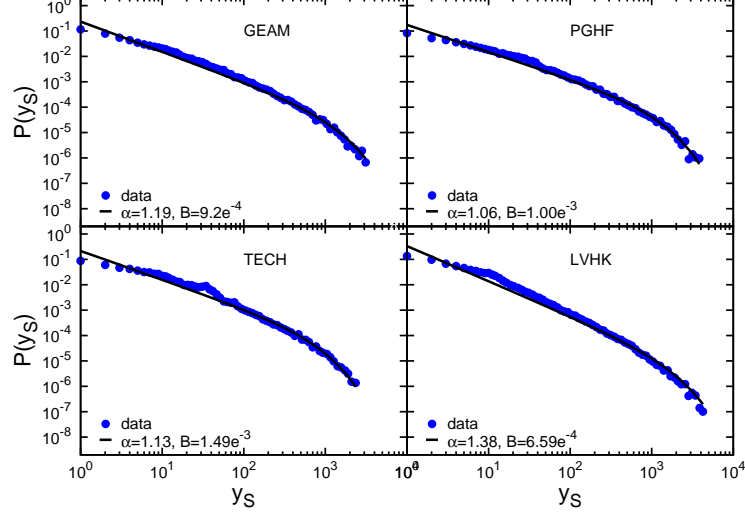


FIG. S2. The probability distribution of time lags between two successive participations of member in group events, y_S , for four selected Meetup groups. The probability distribution follows truncated power-law behaviour $P(y_S) \sim y_S^{-\alpha} \exp(-By_S)$.

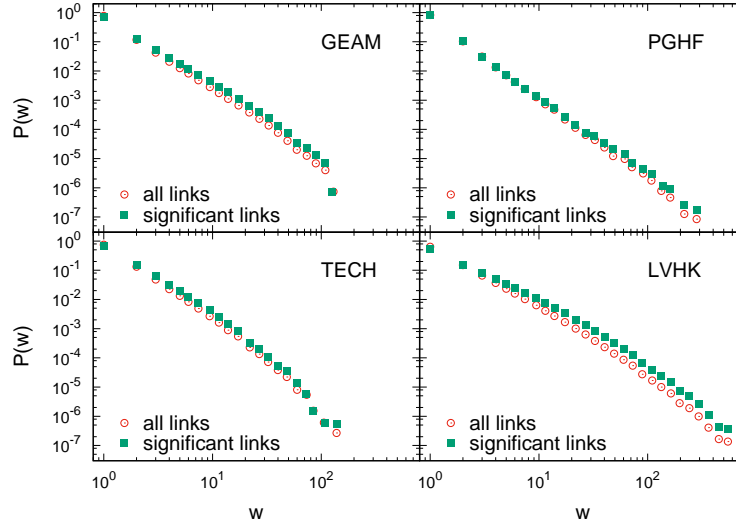


FIG. S3. The probability distribution of link weights in weighted network before and after filtering, for four selected Meetup groups.

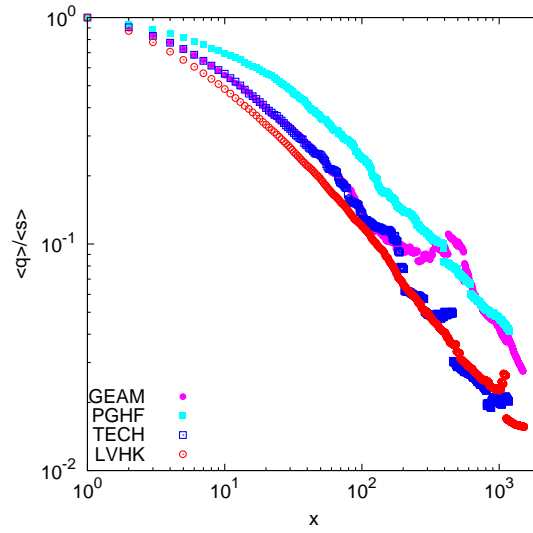


FIG. S4. The dependence of degree strength ratio on the number of participations averaged over all members for four considered Meetup groups.

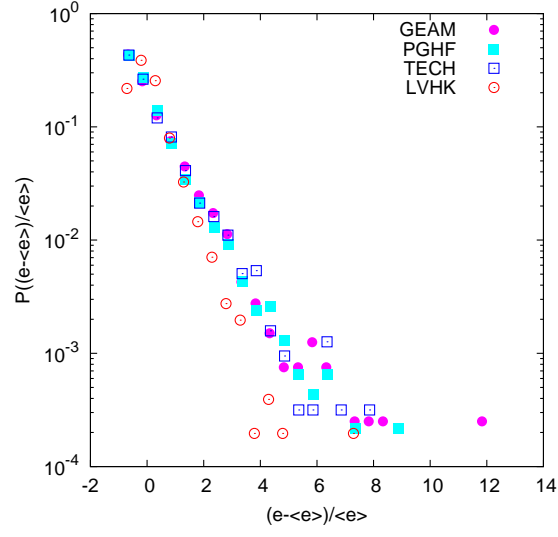


FIG. S5. The probability distribution of relative size fluctuations, $\frac{\langle e \rangle - e}{\langle e \rangle}$, for four considered Meetup groups. e is the event size and $\langle e \rangle$ is average event size.